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Transmission line fault location using traveling wave frequencies and extreme learning machine

Düzgün Akmaz [a,*], Mehmet Salih Mamiş [b], Müslüm Arkan [b], Mehmet Emin Tağluk [b]

[a] Department of Electrical and Electronics Engineering, Engineering Faculty, Munzur University, 62000 Tunceli, Turkey
[b] Department of Electrical and Electronics Engineering, Engineering Faculty, Inonu University, 44280 Malatya, Turkey

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ABSTRACT

In this research, a new approach was proposed for determining the fault location in transmission lines. Traveling wave frequencies and an extreme learning machine (ELM) were used to determine fault location. Transient signals in the time domain were transformed to the frequency domain using the fast Fourier transform (FFT) and the traveling wave frequencies were detected from the transient frequency spectrum. In order to detect the location of fault, traveling wave frequency was used initially to predict the fault location. The prediction of this fault location was tested for many different fault conditions and was found to be adversely affected by only the source inductance value. This is due to the negative effect of source inductance on wave velocity. Regression feature of ELM was used in order to improve the prediction of fault location and to minimize the negative effect of source inductance. For ELM regression training, values of the fault distance estimated from the traveling-wave frequencies and the source inductance values were used as ELM input data, and the actual distance values were used as ELM output data. After ELM regression training, ELM predicted a new fault location using the input data. The Alternative Transients Program (ATP/EMTP) was used to model J. Marti frequency dependent line model, and the MATLAB program was used to perform fault-detection algorithms. Simulation results show that the proposed method is very successful against many variables such as different fault resistances, source inductances, transmission line characteristics, transmission line lengths.

1. Introduction

Determination of the fault locations in transmission lines is important to correct permanent faults in a short time. The last 20 years, along with improvements in computer technology, a lot of fault location methods have been conducted. These fault location methods can be divided into three classes which are based on impedance measurement, traveling wave techniques and artificial intelligence application.

The methods based on impedance measurement are divided into two groups as the phasor domain and time domain. In the methods using phasor domain, the fault distance was predicted by the impedance value calculated through main current and voltage data or through current and voltage phasors [1,2]. The fault distance was determined by solving the differential equations modeled according to the transmission line in the methods using time domain [3,4]. In the application of impedance-based methods, the fact that it only requires data makes it economically advantageous. However, these methods have some disadvantages for example the success of these methods depends on the characteristic of the transmission lines and is influenced by the value of the fault resistance [5].

The methods based on traveling wave theory the fault location was predicted by analyzing the position–time graphs of current or voltage wave movements. Wavelet transfom (WT) [6,7] Teager energy operator [8], S transform [9,10] and FFT [11,12] were used to find fault location. This method has advantages such as its independence from the network configuration and being unaffected by load variance, high grounding resistance and series capacitor. However, in general these systems have the disadvantages of being expensive and requiring high sampling frequency [5].

In addition, some artificial intelligence applications were applied to determine the fault location [13–16]. Artificial neural networks (ANNs) [13], Support Vector Machine (SVM) [14], Wavalet Transform (WT)-Fuzzy Logic [15], WT-ELM, WT-SVM [16] combinations were applied to find fault location.

In this study, a fault location detection algorithm based on traveling wave frequencies and ELM has been developed. Traveling

* Corresponding author.
E-mail address: dakmaz@munzur.edu.tr (D. Akmaz).

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wave frequencies used to find the fault location in some studies in the literature [11,12]. In these studies the FFT tool was used to display the traveling wave frequencies. This method has been applied for many different fault variables and successful results have been obtained. At the same time the fact that the FFT tool does not have the need of high sampling requirement in the study makes this method advantageous compared to the methods using other traveling wave techniques. However, Refs. [11,12] have shown that this fault-location method was adversely affected by only the source inductance values. This is because of the influence of the lumped inductance on the wave speed. The waveform-relaxation method was used to minimize the negative effect of source inductance in Ref. [12].

Unlike other study [12], in this study the regression feature of ELM was used to eliminate the adverse effect of the source inductance value because it provides faster and better performance than single hidden-layer feed-forward neural networks (SLFNNs) and it solves the problems in many different areas [17].

To use the regression feature of ELM, a database with known source inductance values, estimated fault distance values, and actual fault distance values are needed. Therefore, a large number of short-circuit faults (5130-faults) were first realized by using ElectroMagnetic Transients Program/version Alternative Transients Program EMTP/ATP 4.2p1 [18].

Each of the 5130 different short-circuit faults' source inductance value, estimated value of distances with traveling wave frequency, and actual fault distance value were combined in a database. 2610 different short-circuit faults were used for ELM training while 2520 different short-circuit faults were used for the test.

For ELM regression training, the source inductance values and the values of the fault distance predicted by the traveling-wave frequencies constitute ELM input data, and the actual fault distances constitute ELM output data. After ELM training, ELM predicted new fault locations using the input data. All fault data are received from one side of the transmission lines.

Traveling wave frequencies, one of the parameters used in the training and testing of ELM, can be obtained from transient regime current or transient regime voltage signals. However, simulations showed that in some fault cases the traveling waves in the transient regime current are more explicit. Therefore the transient current signals were used in the study.

The completed software has been tested for different parameters such as various fault distances, fault resistances, fault phase angles, different fault types, source inductances and the method was found to be quite successful. At the same time, this completed software was tested to find the fault location in different transmission line with different inductance, capacitance, wave speed and length and very successful results were obtained. This shows that the completed software can be used to locate the fault on different transmission lines without needing any further ELM training. This feature makes the proposed method very useful and advantageous.

In this study, the ATP program was used only to model transmission lines and to obtain transient regime signals. The Matlab program was used for the processing of the signals obtained by the ATPDraw program, the display of the traveling wave frequencies by using FFT, the training and testing of the ELM, the obtain of the neuron-bias values and the fault location algorithm.

2. Traveling-wave theory

Short-circuit events are the most commonly occurring fault situations in transmission lines. A short circuit at any point in the transmission line leads to traveling voltage and current waves on the line. The arrival of these waves from one end of the line to the other is dependent on wave velocity, and the wave parameters of the transmission line determine the wave velocity.

$\upsilon = \lambda f$ is the velocity of wave propagation in km/s, where λ is the wavelength in km and f is the frequency in Hz. The velocity of propagation in terms of the lossless line parameters can be approximated as

$$\upsilon \approx \frac{1}{\sqrt{\iota c}} \tag{1}$$

where ι and c are the inductance and capacitance of the transmission line per unit length, respectively.

τ_f is the travel time from the fault point to the measuring point,

$$\tau_f = \frac{x}{\upsilon}, \tag{2}$$

where x is the distance between the fault point and the measuring point. If the ith transient frequency, f_i, and the wave speed are known, the fault distance can be found using [11,12].

$$x = \upsilon\tau_f = \frac{i\upsilon}{2f_i} \tag{3}$$

3. Extreme learning machine

ELM, proposed by Huang et al. [19], is a fast new method for optimizing single hidden-layer feed-forward neural networks (SLFNNs) and is used for classification and regression problems. ELM randomly selects input weights and analytically determines the weights between the hidden neurons and the output neurons of the SLFNN [16,17,19,20]. Hence, ELM which has a faster learning speed than a conventional technique SLFNN is relatively easy to use for SLFNN [16,17,20]. Any nonlinear activation function, including basis functions such as sine and sigmoid can be used in ELM applications [19].

A standard SLFNN with $\tilde{N}$ hidden nodes formatted with an activation function, $g(x)$, and fed with N arbitrary distinct input samples, can be mathematically modeled as [19].

$$\sum_{i=1}^{\tilde{N}} \beta_i g_i\left(x_j\right) = \sum_{i=1}^{\tilde{N}} \beta_i g\left(w_i . x_j + b_i\right) = o_j, \tag{4}$$

$j = 1, \ldots, N,$

where $w_i = [w_{i1}, w_{i2}, \ldots, w_{in}]^T$ is the input weight vector connecting the i-th hidden nodes and the input nodes, $\beta_i = [\beta_{i1}, \beta_{i2}, \ldots, \beta_{im}]^T$ is the output weight vector connecting the i-th output and the hidden nodes, and b_i is the bias for the i-th hidden node. The hypothesis is that there should exist β_i, w_i, and b_i such that the output of the network matches the desired output, i.e., $\sum_{j=1}^{\tilde{N}} \|o_j - t_j\| = 0$, where $o_j = [o_{j1}, o_{j2}, \ldots, o_{jm}]^T$ is the calculated network output and $t_j = [t_{j1}, t_{j2}, \ldots, t_{jm}]^T \in R^m$ is the desired network output [19]. ELM can also be modeled in matrix form as

$$\mathbf{H}\beta = \mathbf{T}, \tag{5}$$

where

$$\mathbf{H} = \begin{bmatrix} g\left(w_1 . x_1 + b_1\right) & \ldots & g\left(w_{\tilde{N}} . x_1 + b_{\tilde{N}}\right) \\ \vdots & \ldots & \vdots \\ g\left(w_1 . x_N + b_1\right) & \ldots & g\left(w_{\tilde{N}} . x_N + b_{\tilde{N}}\right) \end{bmatrix}_{Nx\tilde{N}} \tag{6}$$